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Restoration of stained old manuscripts via a hybrid wavelet and bilateral filtering system

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Abstract The conservation and restoration of old stained manuscripts is an activity devoted to the preservation and protection of things of historical and personal significance made mainly from paper, parchment, and skin. We present in this paper a hybrid implementation for de-noising and restoration of old degraded and stained manuscripts. This implementation is based on the statistical dependence of the wavelet coefficients of type Ortho-normal Wavelet Thresholding Algorithm based on the principle of Stein's Unbiased Risk-Estimate Linear Expansion of Thresholds (OWT SURE-LET) and the synergy with bilateral filtering. First, the non-biased quadratic risk Stein estimator is applied to de-noise images corrupted by white Gaussian noise. In a second step, an improved bilateral filter is introduced to smooth and eliminate unnecessary details with the advantage of preserving edges between image regions. Obtained results show the effectiveness of the proposed synergy compared to separated approaches both on gray scale images and stained old manuscript.

1. Introduction

In many scientific fields, noise plays a fundamental role; it is the source of many difficulties. The noise in an image is the result of electronic noise from sensors and the quality of the digitizer in addition to long time degradation due to natural attacks. To fight against the effects of noise, it is necessary to make the changes that take into account all image pixels during restoration process.

Recently Luisier and Blu (2007) have taken the principle of linear parameterization which they called LET and generalized it to the SURE-LET method. Donoho and Johnstone (1995) introduced the operator of wavelet coefficients soft thresholding to estimate and minimize the mean square error. This method is now known as Sure-Shrink. The current functions of soft and hard thresholding have proven their effectiveness in many denoising applications. They have been improved by considering non- linear estimators based on linear combinations of elementary functions (Pesquet and Leporini, 1997; Raphan and Simoncelli, 2007). Many works on SURE approaches were conducted in the context of multivariate

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denoising (Benazza-Benyahia and Pesquet, 2005; Chaux et al., 2008) and set-estimation (Combettes and Pesquet, 2004).

Bilateral filtering, which is a denoising technique added to the previous methods for smoothing and removing unnecessary details, is non- linear. It has been proposed in Aurich and Weule (1995) for image smoothing. It found its success in several applications such as image denoising (Tomasi and Manduchi, 1998; Liu et al., 2006), texture manipulation (Oh et al., 2001) compression (Durand and Dorsey, 2002) and photography enhancement (Eisemann and Durand, 2004; Petschnigg et al., 2004). It is also used in other areas such as mesh fairing (Fleishman et al., 2003), volumetric denoising (Wong et al., 2004), optical flow and motion estimation (Xiao et al., 2006), and video processing (Bennett and McMillan, 2005). Authors of Huang et al. (2016) made a quantitative comparison between five denoising algorithms for Chinese calligraphy images filtering.

In paper (Hedjam and Cheriet, 2013), they used multispectral imaging system to restore historical documents for the purpose of their recognition. The author of Alajlan (2010) introduced A novel recursive Algorithm for detail-preserving impulse noise removal.

In this work, the quality of noisy and stained old manuscript images is improved by taking advantages of bilateral filtering and a denoising algorithm based on the combination of the bilateral filter and OWT SURE-LET is proposed. The SURE-LET de-noising approach with ortho-normal wavelets and dependencies between scales (OWT SURE-LET) proposed by Luisier and Blu is used.

2. Denoising based on SURE-LET

Consider a real time signal $\boldsymbol{x}$, with lengths L and L' before and after transformation respectively. This signal is perturbed by a white Gaussian noise centered real $\boldsymbol{b}$ with variance $\boldsymbol{\sigma}^2$ independent of $\boldsymbol{x}$. The actual observed signal is denoted: $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{b}$. The conventional method for reconstructed signal $\hat{x}$ quality assessment is the study of signal to noise ratio (SNR) defined as follows:

$$\mathrm{SNR}(x, \hat{x}) = 10 \times \log_{10}\left(\frac{\|x\|}{\|\hat{x} - x\|}\right) \tag{1}$$

with $\|\hat{x} - x\|$ the square error. It is supposed that $G(y)$ estimates $\boldsymbol{x}$ such that the expectation $E(|\partial g_n(y)/\partial y_n|) < \infty$ for $1 \leqslant n \leqslant L$ (Blu and Luisier, 2007). Then we have:

$$E\left(\sum_{n=1}^{N} g_n(y)x_n\right) = E\left(\sum_{n=1}^{N} g_n(y)y_n\right) - \sigma^2 E\left(\sum_{n=1}^{N} \frac{\partial g_n(y)}{\partial g_n}\right) \tag{2}$$

The function is written as: $G = R\Theta D$ with D, R and Θ are the decomposition, reconstruction and thresholding operators, respectively. The components of G function are written, for all $y \in R^L$ and $1 \leqslant n \leqslant L$. In the other hand, the random variable is given by Blu and Luisier (2007):

$$\varepsilon = \|G(y) - y\|^2 + 2\sigma^2 \mathrm{div}(G(y)) - L\sigma^2 \tag{3}$$

with: $\mathrm{div}(G(y)) = \mathrm{diag}(\mathrm{DR})^T \Theta'(Y)$

$$\Theta'(Y) = \left(\frac{\partial \theta_l(Y_l)}{\partial Y_l}\right) \quad \text{for } L \leq l \leq L'.$$

In addition, by definition:

$$Y_l = (Dy)_l = \sum_{m=1}^{L} D_{l,m} y_m \quad \text{for } L \leq l \leq L'.$$

2.1. SURE-LET denoising algorithm

Now, consider that the estimation function G can be written as a linear combination of K elementary functions G_k:

$$G(y) = \sum_{k=1}^{K} a_k G_k(y) \tag{4}$$

Writing G as a linear combination of elementary functions; each one is being introducing a thresholding function which is a LET part as it is used in Wong et al. (2004). The advantage of this formulation is allowing us to formulate the denoising problem as an optimization problem relatively simple to solve. To get the best possible noise reduction (in the sense of mean square error), it is sufficient to minimize the estimator $\boldsymbol{e}$. To do so, each estimator is considered as a function of the parameter vector $\boldsymbol{a} = (\boldsymbol{a_1}, \ldots, \boldsymbol{a_K})^{\boldsymbol{T}}$. Differentiating this function with respect to each $\boldsymbol{a_K}$, it is possible to rewrite the problem as a linear system to be solved.

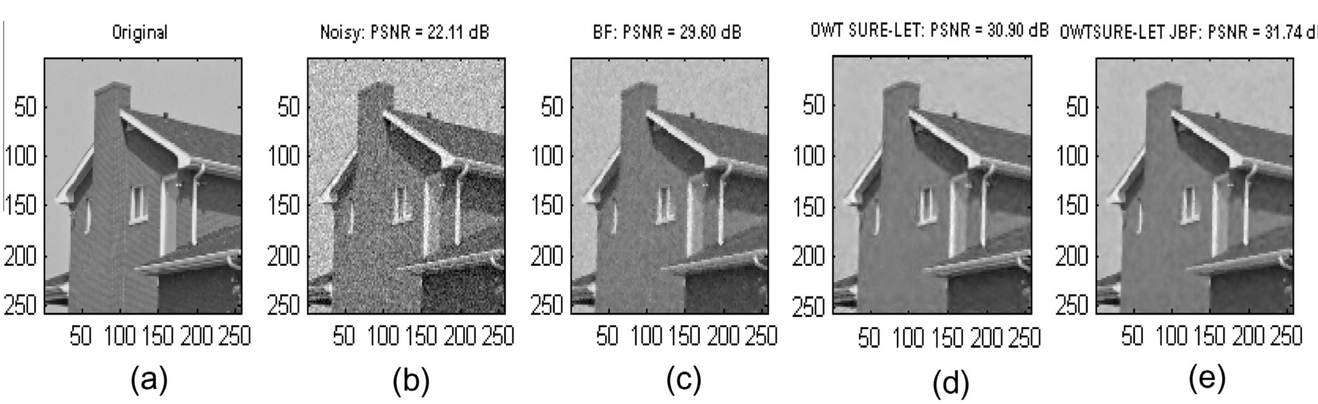

Figure 1 (a) Original image house, (b) noisy image, denoising by: (c) bilateral filtering (d) OWT-SURELET (e) OWT-SURELET JBF.

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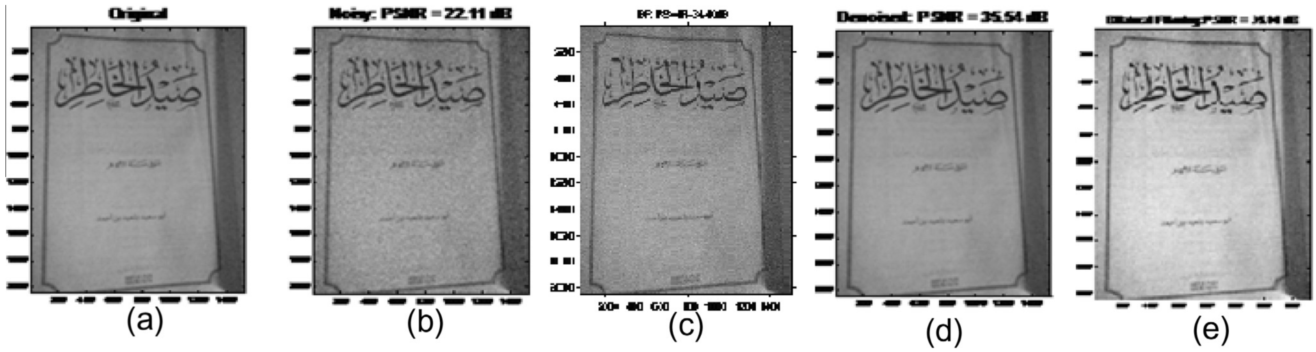

Figure 2 (a) Original image, (b) noisy image, denoising by: (c) bilateral filtering, (d) OWT-SURELET, (e) OWT-SURELET JBF.

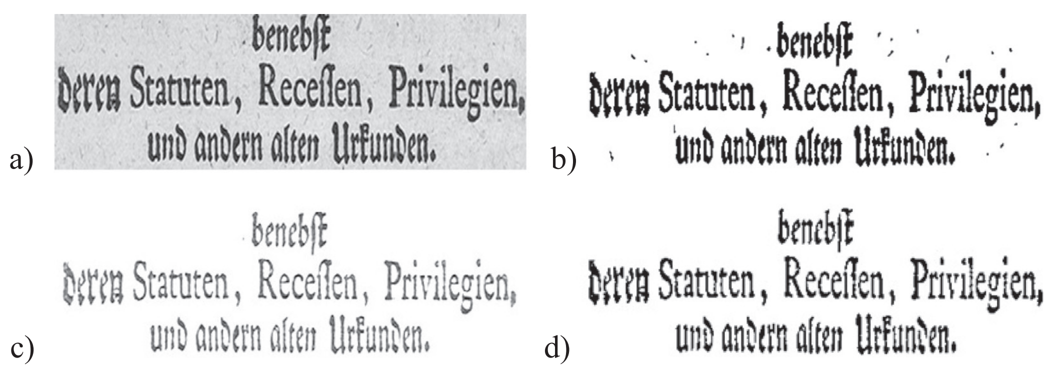

Figure 3 (a) Noisy image, denoising by: (b) bilateral filtering (c) OWT-SURELET (d) OWT-SURELET JBF.

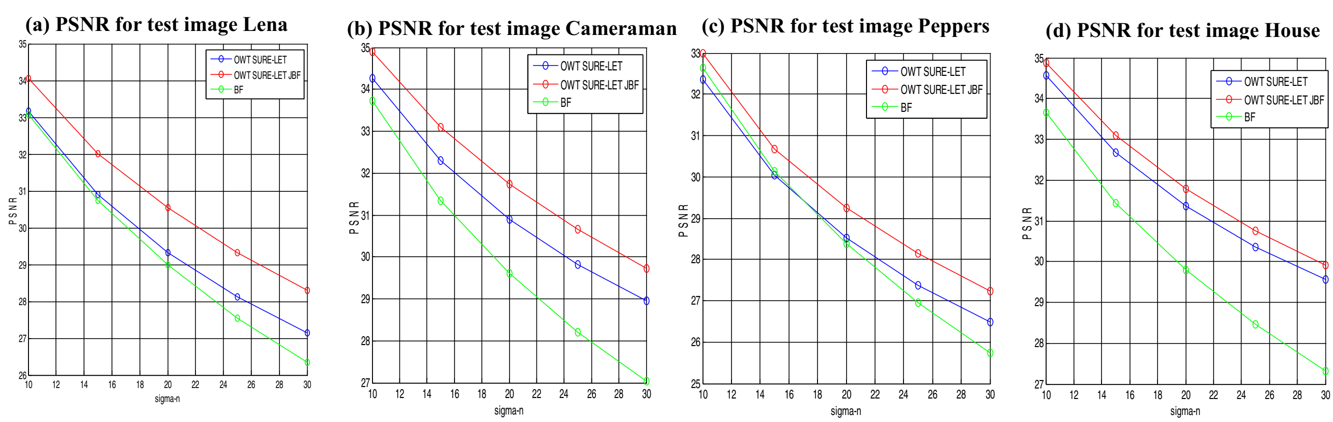

Figure 4 PSNR for images: Lena (a), Cameraman (b), Peppers, (c), House, (d) obtained with OWT SURE-LET, OWT SURE-LET-JBF and BF techniques.

2.2. Minimizing ε

In this section, the work is taken on a linear combination of thresholding functions and look for the parameter vector to let us minimize in this time the estimator ε. We work here with the ***RL*** function:

$$G(y) = \sum_{k=1}^{K} a_k G_k(y) = \sum_{k=1}^{K} a_k R\Theta_k(Dy) \tag{5}$$

Such that $\Theta_k : C^{L'} \to C^{L'}$ corresponds to thresholding punctual functions. Writing the thresholding function $\underline{\Theta}_k : (R^{L'})^2 \to C^{L'}$ defined as follows:

From Eq. (3):

$$\begin{aligned}\varepsilon &= \|G(y) - y\|^2 + 2\sigma^2 \operatorname{div}(G(y)) - L\sigma^2 \\ &= \left\|\sum_{k=1}^{K} a_k G_k(y) - y\right\|^2 + 2\sigma^2 \operatorname{div}\left(\sum_{k=1}^{K} a_k G_k(y)\right) - L\sigma^2 \\ &= J_E(a)\end{aligned} \tag{6}$$

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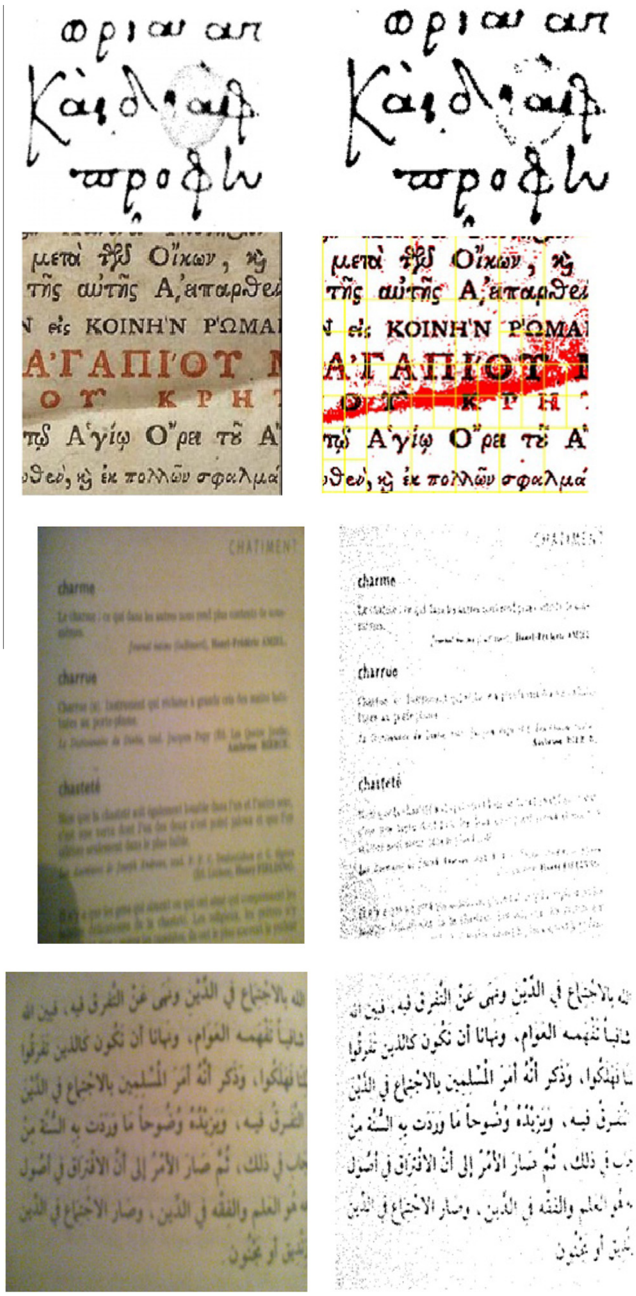

Figure 5 Old stained text restoration with classical binarization.

To de-noise, the vector $\boldsymbol{a}$ minimizing $J_E(a)$ must be found. To do so, we study the quantity $\partial J_E(a)/\partial a_k$:

$$\begin{aligned}\frac{\partial J_E(a)}{\partial a_k} &= \left(\sum_{\ell=1}^{K} a_\ell G_\ell(y) - y\right)^T G_k(y) \\ &\quad + G_k(y)^T\left(\sum_{\ell=1}^{K} a_\ell G_\ell(y) - y\right) + 2\sigma^2 \mathrm{div}(G_k(y)) \\ &= 2\left(\sum_{\ell=1}^{K} a_\ell G_k(y)^T G_\ell(y) - G^{(k)}(y)^T y + \sigma^2 \mathrm{div}(G_k(y))\right)\end{aligned} \tag{7}$$

Then, for $\partial J_E(a)/\partial a_k = 0$, it is found that:

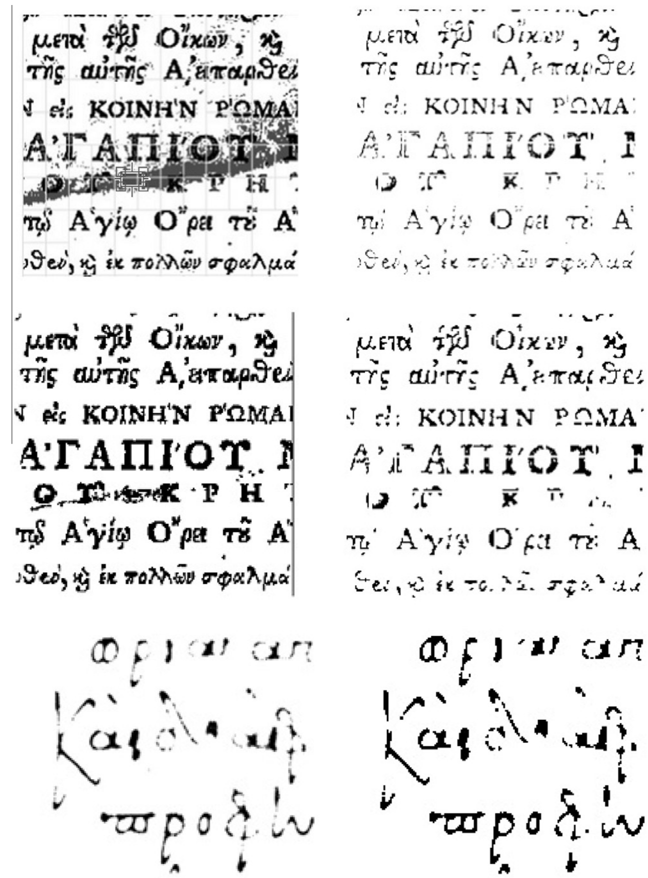

Figure 6 Old stained text restoration with our implementation.

$$\sum_{\ell=1}^{K} a_\ell G_k(y)^T G_\ell(y) = G_k(y)^T y - \sigma^2 \mathrm{div}(G_k(y)) \Longleftrightarrow \widetilde{M} a = \tilde{c} \tag{8}$$

With: $\widetilde{M}_{k,\ell} = G_k(y)^T G_\ell(y)$ and $\tilde{c}_k = G_k(y)^T y - \sigma^2 \mathrm{div}(G_k(y))$, for all $(k,\ell) \in \{1,\ldots,K\}^2$.

3. Denoising hybrid algorithm (OWT_SURELET-JBF)

The bilateral filter as described in Tomasi and Manduchi (1998) is based on a non-linearity to preserve discontinuities and to remove the edge effect. Let $\boldsymbol{u}$ be a noisy image, and (i, j) as the pixel location. $\hat{s}_{i,j}$ is the reconstituted result, may be directly calculated by an average of intensities in the vicinity of the noise $u_{k,\,l}$. The filter formula is:

$$\hat{s}_{i,j} = \frac{\sum_{(k,l)\in\Omega_{N(i,j)}} h_{Dk,l} \cdot h_{Pk,l} \cdot u_{k,l}}{\sum_{(k,l)\in\Omega_{N(i,j)}} h_{Dk,l} \cdot h_{Pk,l}} \tag{9}$$

where $\Omega_{N(i,j)}$ denotes the set of points in the window $(2N + 1) \times (2N + 1)$ centered in (i,j). The function $u_{k,l}$ corresponds to our signal and the function h_D defines the filter as we design classically. The function h_P defines the balance of our samples in filtering process. The principal problem in the classical bilateral filter in image denoising domain is the balance function h_P which cannot be exactly estimated throughout the noisy image.

Table 1 PSNR values with σ_n evolution.

σ_n	10	15	20	25	30	10	15	20	25	30
Lena (512–512)						Cameraman (256–256)				
BF	33.65	31.43	29.79	28.45	27.30	32.64	30.13	28.38	26.95	25.74
OWT_SURELET	34.55	32.67	31.36	30.36	29.55	32.35	30.04	28.51	27.38	26.48
OWT_SURELET-JBF	**34.88**	**33.09**	**31.79**	**30.76**	**29.91**	**32.98**	**30.66**	**29.25**	**28.16**	**27.24**
Peppers (256–256)						House (256–256)				
BF	33.06	30.85	29.00	27.56	26.37	33.72	31.35	29.60	28.19	27.03
OWT_SURELET	33.16	30.90	29.33	28.13	27.15	34.27	32.28	30.90	29.83	28.96
OWT_SURELET-JBF	**34.06**	**32.02**	**30.53**	**29.33**	**28.30**	**34.89**	**33.08**	**31.74**	**30.65**	**29.70**

Table 2 PSNR values with σ_n evolution.

σ_n	10	15	20	25	30	10	15	20	25	30
Fig. 2						Fig. 3				
BF	26.22	24.32	25.07	23.19	22.03	27.01	26.13	24.38	24.15	23.89
OWT_SURELET	26.91	24.08	24.75	24.03	23.06	28.35	27.24	25.51	25.38	24.43
OWT_SURELET-JBF	**27.03**	**26.08**	**25.19**	**24.75**	**23.96**	**28.98**	**27.66**	**25.75**	**25.16**	**24.84**

Authors of Petschnigg et al. (2004) presented a common bilateral filter to calculate the balance function h_P using the instantaneous image in the denoising process. In addition, consider that wavelet based denoising preserves most important details in the image; they can be used as a reference image. In this way, the balance function ***a*** can be estimated more exactly as follows:

$$h_{Pk,l} = e^{-\frac{s^{ref}_{k,l} - s^{ref}_{i,j}}{2\sigma_r^2}} \tag{10}$$

where $\boldsymbol{s^{ref}}$ is the reference denoised image using OWT SURE-LET method, (i,j) is the central pixel and (k,l) is within 3×3 window. h_D is determined by the distance between the neighborhood pixel and the central pixel, where a gaussian function is usually used:

$$h_{Dk,l} = e^{-\frac{(k-i)^2+(l-j)^2}{2\sigma_D^2}} \tag{11}$$

The parameter σ_D characterizes the spatial behavior of the bilateral filter. This parameter changes with noise level changes and the size of Ω_N and σ_n. Particularly, when the noise level is high.

$$\varepsilon_{i,j} = \frac{\sum_{(k,l)\in\Omega_N(i,j)} h_{Dk,l} \cdot h_{Pk,l} \cdot (u_{k,l} - s_{k,l})}{\sum_{(k,l)\in\Omega_N(i,j)} h_{Dk,l} \cdot h_{Pk,l}} \tag{12}$$

For $\varepsilon_{i,j} = 0$, the common bilateral filter performs well noise suppression. However, the equation is not completely established, which causes, thus noise stains.

Author of Elad (2002) presented a penalty function to simplify $\varepsilon_{i,j}$ which can be directly estimated as follows:

$$\hat{\varepsilon}_{i,j} = \frac{\sum_{(k,l)\in\Omega_N(i,j)} h_{Dk,l} \cdot h_{Pk,l} \cdot (u_{k,l} - s^{ref}_{k,l})}{\sum_{(k,l)\in\Omega_N(i,j)} h_{Dk,l} \cdot h_{Pk,l}} \tag{13}$$

This compensation limit is added in the common bilateral filter in order to suppress stains:

$$\hat{s}_{i,j} = \frac{\sum_{(k,l)\in\Omega_N(i,j)} h_{Dk,l} \cdot h_{Pk,l} \cdot u_{k,l}}{\sum_{(k,l)\in\Omega_N(i,j)} h_{Dk,l} \cdot h_{Pk,l}} - \beta\hat{\varepsilon}_{i,j} \tag{14}$$

With $\beta \in [0, 1]$ in the best case.

The experimental results prove that the best interval for the three parameters is: $\beta = [0.5, 0.8]$, $\sigma_d = [1.5, 1.8]$ and $\sigma_r = \sigma_n$. To simplify, it is used in this work: $\beta = 0.5$, $\sigma_d = 1.5$ and $\sigma_d = 2\sigma_n$.

4. Results and discussion

In this section, the interest of the developed approach for reducing noise in degraded and stained old manuscript images is illustrated and the obtained simulation results are presented. The noise is considered an additive white Gaussian noise with zero mean and variance σ^2. We have chosen the test images: Lena, Cameraman, Peppers and House at decomposition scale of four and the analyzing wavelet is at sym8. Figs. 1–3 show the resulting images for each denoising method with a standard deviation $\sigma = 20$. Note that the visual quality of our algorithm is higher than other denoising methods. The mean and standard deviation (in 50 simulation runs) of the output image PSNR, given using various methods for the three test images are compared in Fig. 4. The PSNR is calculated for each input value of σ_{in} in the range {10–28}. It is found that the proposed algorithm outperforms other denoising techniques, noting that it is even more efficient compared to OWT – SURE-LET, and the PSNR is important. In addition, it is remarkable that the bilateral filter (BF) proves less efficient compared to other methods for low PSNR range, see in Figs. 5 and 6 a comparison between classical binarization and our implementation of old stained text restoration. For a better comparison, the average PSNR for test images: $\sigma_n = 5$, 10, 15, 20, 25 and 30 is calculated in Table 1 for test images and Table 2 for old manuscript images. The value of PSNR is significantly improved by the proposed algorithm.

5. Conclusion

In this work, a hybrid (OWT SURE-LET-JBF) denoising algorithm for hardly degraded and stained old manuscripts, based on SURE-LET and the bilateral filter is implemented. The principle of SURE-LET estimator in the wavelet transform domain is given, and then, a hybrid implementation which combines the denoising estimator OWT SURE-LET and bilateral filtering is proposed. The algorithm can be summarized in four basic steps:

- Apply the wavelet transform on the noisy data.
- Estimate the wavelet coefficients by the SURE-LET estimator.
- Reconstruct the reference image by calculating the inverse wavelet transform from the estimated coefficients.
- Apply bilateral filter on the reference image to get the final denoised image.
- The results showed the effectiveness of the proposed noise reduction approach. This is possible by making a judicious choice of the wavelet basis and the resolution level. In conclusion, the association OWT SURE-LET algorithm and bilateral filter leads to a robust preprocessing.

References

Alajlan, Naif, 2010. A novel recursive algorithm for detail-preserving impulse noise removal. J. King Saud Univ. – Comput. Inf. Sci. 22, 37–44.

Aurich, V., Weule, J., 1995. Non-linear Gaussian filters are performing edge preserving diffusion. In: Proceedings of the DAGM Symposium, pp. 538–545.

Benazza-Benyahia, A., Pesquet, J.-C., 2005. Building robust wavelet estimators for multicomponent images using Stein's principle. IEEE Trans. Image Proc. 14 (11), 1814–1830. 118.

Bennett, Eric P., McMillan, Leonard., 2005. Video enhancement using per-pixel virtual exposures. ACM Trans. Graphics 24 (3), 845–852. Proceedings of the SIGGRAPH Conference.

Blu, T., Luisier, F., 2007. The SURE-LET approach to image denoising. IEEE Trans. Image Process. 16 (11).

Chaux, C., Duval, L., Benazza-Benyahia, A., Pesquet, J.-C., 2008. A nonlinear Stein based estimator for multichannel image denoising. IEEE Trans. Signal Process. 56 (8).

Combettes, P., Pesquet, J.-C., 2004. Constraint construction in convex set theoretic signal recovery via Stein's principle. In: Proc. Int. Conf. on Acoust., Speech and Sig. Proc., vol. 2, pp. 813–816, Montréal, Canada. 118, 2004.

Donoho, D.L., Johnstone, I.M., 1995. Adapting to unknown smoothness via wavelet shrinkage. J. Am. Stat. Assoc. 90 (432), 1200–1224.

Durand, F., Dorsey, J., 2002. Fast bilateral filtering for the display of high dynamic-range images. ACM Trans. Graphics 21 (3), 257–266. Proceedings of the ACM SIGGRAPH conference, 2002.

Eisemann, E., Durand, F., 2004. Flash photography enhancement via intrinsic relighting. ACM Trans. Graphics 23. Proc. of SIGGRAPH Conference.

Elad, M., 2002. On the bilateral filter and ways to improve it. IEEE Trans. Image Process. 11 (10), 1141–1151.

Fleishman, Shachar, Drori, Iddo, Cohen-Or, Daniel, 2003. Bilateral mesh denoising. In: ACM Transactions on Graphics, 22(3), July 2003. Proceedings of the SIGGRAPH Conference.

Hedjam, Rachid, Cheriet, Mohamed, 2013. Historical document image restoration using multispectral imaging system. Pattern Recogn. 46 (8), 2297–2312.

Huang, Zhi-Kai, Li, Zhi-Hong, Huang, Han, Li, Zhi-Biao, Hou, Ling-Ying, 2016. Comparison of different image denoising algorithms for Chinese calligraphy images. Neurocomputing 188 (5), 102–112.

Liu, C., Freeman, W.T., Szeliski, R., Kang, S., 2006. Noise estimation from a single image. In: Proceedings of the Conference on IEEE Computer Vision and Pattern Recognition, vol. 1, pp. 901–908.

Luisier, F., Blu, T., 2007. SURE-LET multichannel image denoising: interscale orthonormal wavelet thresholding. IEEE Trans. Image Proc. 118, 147.

Oh, B.M., Chen, M., Dorsey, J., Durand, F., 2001. Image-based modeling and photo editing. In: Proc. of SIGGRAPH conference, ACM.

Pesquet, J.-C., Leporini, D, 1997. A new wavelet estimator for image denoising. In: IEE Sixth International Conference on Image Processing and its Applications, vol. 1, pp. 249–253 (118, 148, 1997).

Petschnigg, G., et al., 2004. Digital photography with flash and no-flash image pairs. In: Proc. SIGGRAPH, pp. 664–672.

Raphan, M., Simoncelli, E.P., 2007. Learning to be Bayesian without supervision. In: Schölkopf, B., Platt, J., Hofmann, T. (Ed.), Proc. Neural Information Processing Systems, Vancouver, BC, Canada. Published as Advances in Neural Information Processing Systems, vol. 19, May 2007. 118 2006.

Tomasi, C., Manduchi, R., 1998. Bilateral filtering for gray and color images. In: Proceedings of the IEEE International Conference on Computer Vision, pp. 839–846.

Wong, Wilbur C.K., Chung, Albert C.S., Yu, Simon C.H., 2004. Trilateral filtering for biomedical images. In: Proceedings of the International Symposium on Biomedical Imaging. IEEE.

Wong, W.C.K., Chung, A.C.S., Yu, S.C.H., 2004. Trilateral filtering for biomedical images. In: Proc. of International Symposium on Biomedical Imaging, IEEE.

Xiao, Jiangjian, Cheng, Hui, Sawhney, Harpreet, Rao, Cen, Isnardi, Michael, 2006. Bilateral filtering-based optical flow estimation with occlusion detection. In: Proceedings of the European Conference on Computer Vision.

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